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NEURO-FUZZY ARCHITECTURE OF THE 3D MODEL OF MASSIVE PARALLEL ACTUATORS

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ABSTRACT

This paper reports the effective control mechanism of the discrete state manipulators (DSMs) with six degree of freedom (DOF). The DSMs are special kind of robot manipulator with massive actuators that can be switched among limited number of discrete states. We introduce ternary-DSMs (t-DSMs) manipulators which controlled by force and have continuous motions that commanded through only three discrete states. The main problem of this mechanism is how to design a real-time controller which is efficient and fast for solving its inverse static problem (ISP). Precisely, a computational intelligence method based on neuro-fuzzy method is suggested to find the optimal training computation, which is measured by the root mean squared error of ISP. The architecture of t-DSMs featuring three-state force pneumatic actuators and six-DOF. For instance, a neuro-fuzzy method for t-DSMs constructs IF-THEN rules from fuzzy relations among inputs and outputs in the training mechanism (inputs: position and force; outputs: three-state). After related model is found in the training phase, the architecture can be used to determine outputs of the network from given inputs with similar accuracy in the testing phase. The paper proposed an architecture which is based on the Neuro-Fuzzy Takagi Sugeno (NFTS) inference scheme with Gaussian membership functions. The structure is with multivariate input and multi-state outputs, such as positions and forces as input NFTS networks and the three-state of the actuators as output networks. The learning of the network uses an extended LMA version with optimal training parameters. The training algorithm needs at least one million iterations with different membership functions; employ around 17% of the input-output correspondences dataset from the known input and output. For training database, the NFTS model generates 124 dataset from the 729 possible dataset. The optimized membership function (*M*) after one week searching time using optimized search procedure using *M* from 4 to 15 for the 6-DOF model of 6-ternary DSMs. Regarding model performances for the ISP solution, the NFTS with *M*=9 features better root mean squared error results compared to the others.

Keywords: three-state force actuators, inverse static problem (ISP), neuro-fuzzy control, 6-ternary DSMs.

INTRODUCTION

This paper proposes an effective way to control the ternary-Discrete State Manipulator (t-DSMs) through the real-time Neuro-Fuzzy controller. The t-DSMs are a special kind of mechanisms whose actuators can only be switched among three states (extended, null and retract, can be explained as +1, 0 and -1). Furthermore, the t-DSMs are a kind of manipulators in an effort to reduce the control procedure and complexity of computer interfacing.

At this time, t-DSMs can be hardly clustered into two categories depending on their actuators act as discrete generators for displacement or discrete generators for force. For instance, the first type of binary DSMs is the binary snake-like robots (SLRs). The SLRs are proposed by Chirikjian et al., ([1], [2], [3], [4]) and Dubowsky et al., ([5], [6]), which are kinematically constrained mechanisms employing a large number of discrete actuators in series-parallel configuration. The discrete actuators can be configured either fully extended, just follow or fully contracted without consideration of the supplementary forces acting on them. In addition, the second type t-DSMs are the Massively Parallel Actuators (MPAs), or sometimes called as Massively Parallel Robots (MPRs). Here, the MPRs are dynamically constrained robots exhausting a large number of binary or ternary pneumatic actuators with constant force or no force [7].

For achieving accuracy in high position/force abilities, the SLRs or MPRs model practically needs a large number of discrete actuators (by experiment around 4-10 times larger than the number of desired DOF for the manipulator). The position of the actuators can be organized in a series-parallel formation [1], [5] or in parallel configuration [7].

Moreover, the ISP of t-DSM type MPRs model is usually very difficult to solve and needs unique solution. The optimal results or solutions practically require complicated processes. In the past, some significant research efforts have been devoted to address the inverse static problem (ISP), such as: combinatorial heuristics algorithms [5]; theory of probabilistic [3]; comprehensive brute-force search methods [7]; optimized programming by genetic approach [6]; Hopfield networks and Boltzmann machines algorithms [7]. Despite the fact that most of the suggested schemes or solutions are formally very effective to reduce the complexity problem, such as: the calculation time from exponential to polynomial time. The result of the algorithms still has numerous mathematic calculations, especially if the algorithms are applied to the real-time control mechanism.

NEURO-FUZZY METHOD FOR REAL-TIME CONTROL SOLUTION

This paper introduces the efficient real-time mechanism to control the state of discrete manipulators via computational intelligence methods. Here, the potentialities of using computational intelligence algorithm such as neuro-fuzzy (NF) method as the real-time solution of the ISP of ternary-DSMs are investigated. The proposed DSMs feature six degree of freedom actuated by six force generators with double action valve control. The positions of actuators are placed in parallel with symmetrical configuration which are extended version of massive parallel arrays in 1-DOF [8] and 6-DOF [9].

For more information, NF networks are hybrid networks between humans as rational fuzzy logic with the learning ability of neural networks. This idea is coming because of the main advantages of a NF system are: it interprets IF-THEN rules from input-output connections and focuses on reducing the generalization error in the training phase; In addition, it has efficient calculation time on the online phase. This idea was first suggested by J. Jang [10] and was later developed by Palit [11], [12].

In the next section, we proposed t-DSMs mechanism with real-time controlled. The control part uses Neuro-Fuzzy Takagi-Sugeno (NFTS) inference system with Gaussian membership functions (GMFs). Concerning the ISP, the proposed model can be applied in finding the optimal number of membership functions (*M*) that provide a strong link between the input values α with their output variables ternary number $u = [u_1, \ldots, u_6]$. In the design of the architecture of the NF, the *M* will be changed in the learning process using different *M* from 4 to 15.

TERNARY-DISCRETE STATE MANIPULATORS MECHANISM (t-DSMs)

Moreover, Figure-1 exploits the t-DSMs mechanism that is considered in this paper. It has 6 identical pneumatic actuators respectively 6-SPS-3D mechanism. The terms S, P and S are for spherical, prismatic and spherical joints respectively, sharing the same moveable platform (*C*) through their moving joint. The moveable platform is hinged to the platform at origin *B* (in the center of platform), links to m variable length *Ci*-*Bi*, where i = 1, 2, ..., *p* ; here *p* = 6. The moving platform are hinged at the points of the common platform based *Bi* and displacement of points of the *Ci* platform respectively, correspondingly relative to the XYZ axis along to the both platform. In order to neglect the twist of the moving platform while aactivating the actuators, additional crank and slotted-lever in the centre of both platforms are applied. Moreover, the description about the t-DSMs mechanism can be shown in Table-1. The implementation mechanisms possibly will be achieved by using six double acting pneumatic cylinders with bi-directional control valves.

NEURO-FUZZY ARCHITECTURE

This Section presents the architecture for the new model of t-DSMs, like shown in Figure-2. The architecture is called as feedforward Neuro-Fuzzy Takagi-Sugeno (NTFS), type multi-input multi-output. The inputs are six set of coordinates XYZ and Forces in the related coordinate direction while the outputs consist of the states of the actuators (U_{State}). It also uses GMFs in the fuzzyfication phase.

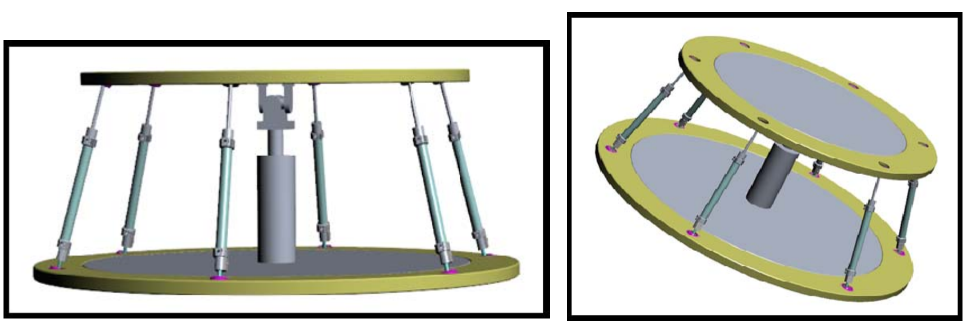

Figure 1. Design of t-DSMs with 6 actuators

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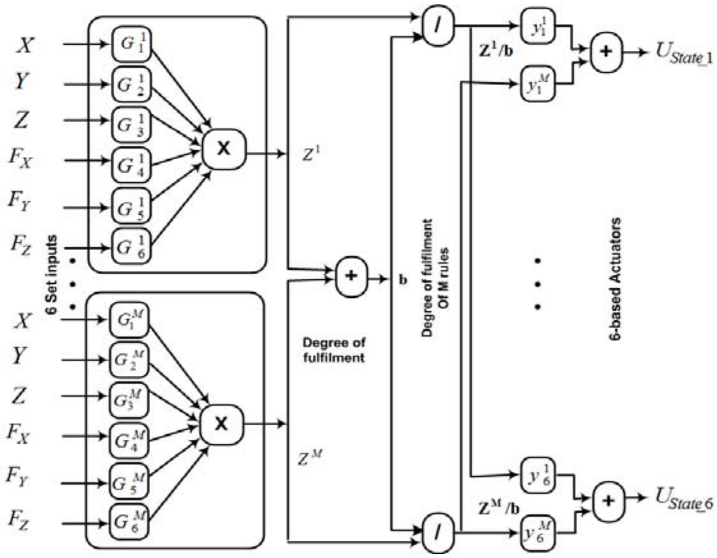

Figure-2. Feedforward Neuro-Fuzzy network type Takagi-Sugeno, No. Of input-output = 6-6, Optimized Membership Function M = 9, learning method: LMA.

Table-1. Description of t-DSMs with 6 actuators.

Description	Quantity	Unit/Type
Mass	**30067.67**	**Grams**
Diameter		
Top Plate	800	Mm
Bottom Plate	1000	Mm
Material		
Top Plate	plastic	EPDM
Bottom Plate	aluminum	6063-T6
Actuator		
Number of actuators	6	each
Distance between actuators	60	Degrees
Stroke	180	Mm
Actuator Joints		
Type	Spherical Joint	
Distance from center of plate		
Bottom plate	460.00	Mm
Top plate	360.00	Mm

Moreover, we introduce the GMFs (1) as fuzzyfication functions to the NF methods G_y^n (j = 1, 2; n = 1, …, 6), for input pairs $\alpha^D = [P^X, P^Y, P^Z, F^X, F^Y, F^Z]$, where α^D are the input set of the positions (P^X, P^Y, P^Z) and the forces (F^X, F^Y, F^Z) of the moving platform with respect to the XYZ Euler coordinates.

$$G_y^n(\alpha_y) = \exp\left(-\left[(\alpha_y - c_y^n)/\sigma_y^n\right]^2\right) \qquad (1)$$

with parameters means c_y^n and variance σ_y^n together with the corresponding n-fuzzy rules (FR^n) can be written as:

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$$FR^n: IF\ \alpha_1 is\ G_1^n\ AND\ \alpha_2 is\ G_2^n\ AND\ ...$$
$$THEN\quad y_i^n = w_{0i}^n + w_{1i}^n\alpha_1 + ... \qquad (2)$$

Here w_{0i}^n, w_{1i}^n being the Takagi-Sugeno weights (for i = 1, …, 6, and n = 1, …, M, M is the number of optimized rules for the proposed model, M = 9 will be found by search mechanism), the last part of the considered Neuro-Fuzzy model calculates the output variables $\bar{u}$.

$$\bar{u} = \sum_{n=1}^{M} y_i^n \left(\frac{\prod_{y=1}^{6} G_y^n(\alpha_y)}{\sum_{n=1}^{M} \prod_{y=1}^{6} G_y^n(\alpha_y)} \right) \qquad (3)$$

The NF output (3) consits of six outputs and still in the real form. Moreover, the outputs will be derived by alternatively approximating the activation states of actuators u_i through the following threshold function:

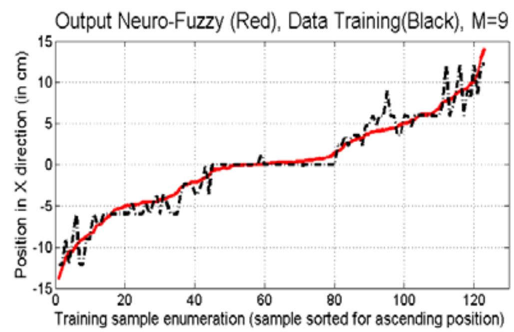
$$u_i = round(\bar{u}_i) \qquad (4)$$

where *round* indicates a process to change real form of $\bar{u}$ into the three state numbers which are -1, 0 and +1. In the process to find the predicted outputs, NFTS model requires the tuning of the parameters c_y^n, σ_y^n, w_{0i}^n, w_{yi}^n (here y = 1, 2, ..,6; i = 1, 2,..., 6; n = 1, …, M;). The number of parameters for the considered architecture (with M=9) is 486 parameters from four tuned parameters. The values of these parameters are found by an optimized learning procedure. The learning procedure employs 17% of the input-output correspondences known from Δ dataset for the 6-ternary DSMs respectively.

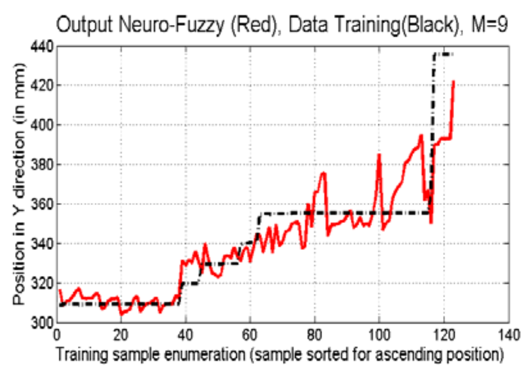
Moreover, the fuzzy logic system, once represented as the equivalent Multi-Input Multi-Output feed forward network, can generally be trained using any suitable training algorithm, such as standard Backpropagation Algorithm (BPA) and a second order learning algorithm, called as the Levenberg-Marquardt Algorithm (LMA) [12]. Because BPA has slow speed of convergence in the learning phase and needs to be further improved, we prefer to propose LMA. It is well-known that LMA is actually a second order learning algorithm that is based on modified Newton's method and uses Jacobian matrix's matrix in order to estimate the second-order partial derivatives of each updated parameter equations. Detailed procedure of learning phase and mathematic equations are described in [13].

RESULTS

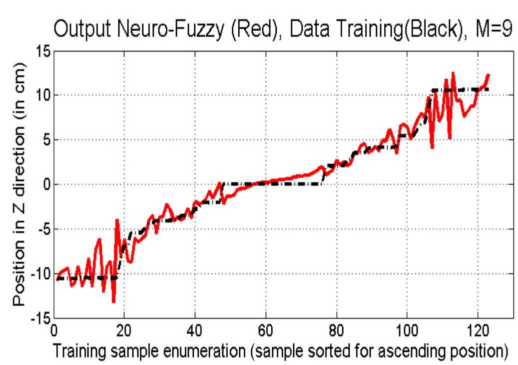
The best parameters of NF architecture, i.e. c_y^n, σ_y^n, w_{0i}^n, w_{yi}^n are be updated in the training algorithm. The simple search procedure is needed in order to find the optimized number of rules M for the six ternary-DSMs mechanism. This procedure is a local search method that tries to find the best local minimum from one million iterations on the learning procedures. The procedure permits the best learning parameters that minimize the total error training (e_t) in every iteration and neglects the parameters that caused bigger e_t. The optimized membership function (M) is achieved after one week of searching time. As the results, the optimized model that give best performance is M= 9 for the 6-ternary MPRs, with model performances for the ISP solution shows off-line trained t_{off} = 3.2e3s, and RMSE model e_t = 6.14 % For the training purposes, the NTFS method uses 124 data training. The comparison between data and prediction of training performance of Neuro-Fuzzy method can be seen on Figure-3 and Table-2. The results in Figure 3 also shown that model has ability to predict the forces accurately but with less ability in predicting the positions.



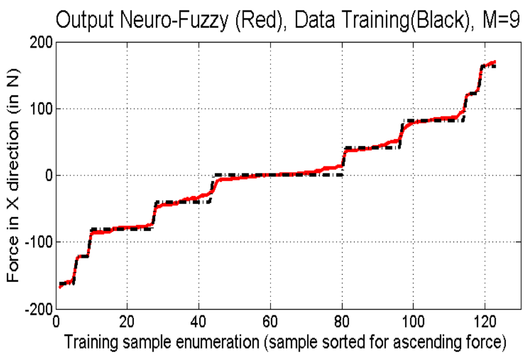
(a) Training Performance of Position in X Direction



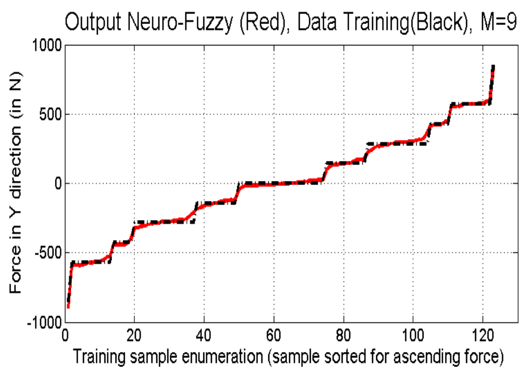
(b) Training Performance of Position in Y Direction



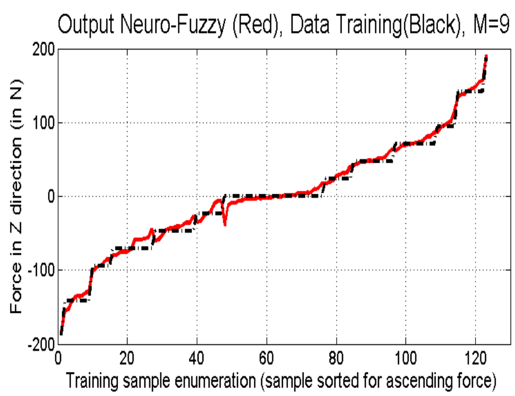
(c) Training Performance of Position in Z Direction



(d) Training Performance of Force in X Direction



(e) Training Performance of Force in Y Direction



(f) Training Performance of Force in Z Direction

Figure-3. Training performance of 6-ternary 3D-MPRs with Neuro-Fuzzy Method with *M*=9. (a) Position in X (b) Position in Y (c) Position in Z (d) Force Fx (e) Force Fy (f) Force Fz.

Table-2. Performance Results of t-DSMs model with different Membership Function (*M*).

No. Membership Function M	RMSE Training In %	Off-line Trained (sec)
4	7.99	2.558.7
5	8.15	2667.7
6	8.20	2993.2
7	8.13	3045.8
8	7.58	3162.3
9	6.14	3218.4
10	7.84	3314.2
12	7.13	3502.6
15	8.50	3788.9

CONCLUSIONS

This paper presented six-DOF discrete state manipulators with 6 pneumatic actuators with three-state force generators, called as t-DSMs. An optimized model of Neuro-Fuzzy method type Takagi-Sugeno is found using Levenberg Marquardt learning algorithm for the solution of inverse static problem of the considered t-DSMs. In addition, compared to the standard manipulator array mechanism, the partitioned and parallel distributed actuator architecture proved that the considered discrete manipulator features sufficient and accurate force generation abilities. The results show that NFTS with membership number (*M*) = 9 features better generalization ability compared to the other number of *M* during the off-line phase.

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